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Does Idiosyncratic Risk Matter: Another Look

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Abstract

We show that the equal-weighted average stock volatility analyzed by Goyal and Santa-Clara (GS, 2003) forecasts stock returns because of its co-movements with stock market volatility. Moreover, contrary to the positive relation hypothesized by GS and many others, we find that the value-weighted average stock volatility is *negatively* related to future stock returns when combined with stock market volatility. This puzzling result reflects the fact that the value-weighted average stock volatility is negatively correlated with the consumption-wealth ratio, and its predictive power vanishes if we control for the latter in the forecasting equation. The idiosyncratic volatility proposed by GS thus provides no information beyond the forecasting variables advocated by Guo (2003).

Keywords: Idiosyncratic Stock Volatility, Stock Market Volatility, Consumption-Wealth Ratio, and Stock Return Predictability.

JEL number: G1.

In a recent paper, Goyal and Santa-Clara (GS, 2003) propose a measure of the equal-weighted *monthly* average stock volatility using the CRSP (Center for Research in Security Prices) daily return data:

$$(1) \qquad EWIV_t = \frac{1}{N_t}\sum_{i=1}^{N_t}[\sum_{d=1}^{D_{it}} r_{id}^2 + 2\sum_{d=2}^{D_{it}} r_{id} r_{id-1}],$$

where N_t is the number of stocks, D_{it} is the number of trading days for stock *i* in month *t*, and r_{id} is the return on stock *i* in day *d* of month *t*.[1] GS show that EWIV has some forecasting abilities for excess stock market returns. However, in contrast with the Capital Asset Pricing Model (CAPM), a measure of the *monthly* stock market volatility,

$$(2) \qquad MVGS_t = \sum_{d=1}^{D_t} r_{md}^2 + 2\sum_{d=2}^{D_t} r_{md} r_{md-1},$$

where r_{md} is the stock market return in day *d* of month *t*, doesn't forecast stock returns. Given that most variations of EWIV are due to idiosyncratic shocks to individual stocks, GS conclude that, consistent with the early authors, e.g., Lehmann (1990), idiosyncratic risk is an important determinant of conditional excess stock market returns.

The results by GS, however, need further investigation because recent authors, e.g., Scruggs (1998), Guo (2002), uncover a positive risk-return tradeoff in the stock market after controlling for the hedge component in the intertemporal CAPM (ICAPM) advocated by Merton (1973). In particular, Guo (2002) shows that, in conjunction with the consumption-wealth ratio by Lettau and Ludvigson (2001), a measure of the quarterly stock market volatility similar to equation (2) is a strong predictor of excess stock market returns. These results are also consistent with the limited stock market participation model by Guo (2003). He argues that conditional excess stock market returns have two components: a risk component, as in the CAPM, and a liquidity component tracked by the consumption-wealth ratio. Because these two components can be negatively related to one another, we might fail to find a positive risk-return relation if we don't control for the liquidity component.

Therefore, the results by GS might suggest two things. First, the idiosyncratic volatility forecasts stock returns because it captures the effect of non-traded human capital on asset prices, as stressed by Guo (2003), among many others. For example, it co-moves with the liquidity component approximated by the consumption-wealth ratio. Second, as argued by Levy (1978), Merton (1987), and Malkiel and Xu (2001), the idiosyncratic volatility matters because many investors hold poorly diversified portfolios. Therefore, investors might demand a premium on idiosyncratic risk, in addition to the market risk and liquidity risk premiums. To test the undiversified portfolio hypothesis, we investigate in this paper whether the idiosyncratic volatility proposed by GS provides information about future stock market returns beyond stock market volatility and the consumption-wealth ratio.

We first confirm that the average stock volatility EWIV forecasts one-quarter-ahead stock market returns over the 1962:Q4 to 1999:Q4 period analyzed by GS.[2] In dramatic contrast with GS, who use the monthly data, EWIV becomes insignificant if we add stock market volatility to the forecasting equation.[3] This result indicates that, as discussed in footnote 2, stock market volatility is more precisely estimated over a relatively long interval such as a quarter than

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[1] Campbell et al. (2001) advocate a volatility measure very similar to equation (1). We define a quarterly volatility measure below by setting t to be a quarter rather than a month.

[2] We use a quarterly sample rather than the monthly sample use by GS because the consumption-wealth ratio is reliably available only on a quarterly basis. Moreover, Ghysels, Santa-Clara, and Valkanov (2003) argue that investors tend to place more weight on realized daily returns of the distant past than those of the recent past when forming expectations about stock market volatility. Therefore, stock market volatility is likely to be more precisely measured at the quarterly frequency than the monthly frequency. However, to be comparable with GS, we use the monthly EWIV of the last month in each quarter to forecast one-quarter-ahead excess stock market returns, although we find qualitatively the same results using quarterly EWIV.

[3] We use the same measure of stock market volatility used by Guo (2002): The sum of the squared deviation of the daily excess stock market returns from its quarterly mean in a quarter. This is also the volatility measure advocated by Merton (1980). However, we find very similar results using stock market volatility defined in equation (2).

over a relatively short interval such as a month.[4] Interestingly, although EWIV by itself becomes insignificant if we extend the sample to 2002:Q4 by adding 12 quarterly observations, it regains the significance when combined with the consumption-wealth ratio. However, these results merely reflect the fact that EWIV co-moves with stock market volatility: It loses the predictive power again if we control for the latter in the forecasting equation. Therefore, the equal-weighted average stock volatility investigated by GS does not provide information about future stock returns beyond stock market volatility.

For robustness, we also analyze a value-weighted average stock volatility (VWIV), which is a potentially better measure of idiosyncratic risk faced by investors than EWIV but is not considered by GS.[5] Over the sample period 1963:Q1 to 2002:Q4, although VWIV by itself has no forecasting power for future stock returns, it is significantly *negative* in the forecasting equation when combined with stock market volatility. This negative relation between the idiosyncratic risk and expected returns is in sharp contrast with the positive relation uncovered by GS for the equal-weighted average volatility and is also at odds with the existing theories mentioned above.[6] One possible explanation is that, as mentioned above, VWIV might be correlated with the liquidity premium advocated by Guo (2003). Indeed, its predictive ability disappears if we also add the consumption-wealth ratio to the forecasting equation. These results are robust to a host of alternative measures of the idiosyncratic volatility. Therefore, the conclusion by GS—that the idiosyncratic volatility measured in equation (1) or its value-weighted equivalent matters—should be interpreted with caution.

[4] Similarly, Guo and Whitelaw (2003) show that using the implied volatility derived from option contracts on the S&P 100 index (an efficient measure of stock market volatility) helps uncover a positive risk-return tradeoff in the stock market.

[5] Yan and Zhang (2003) find that VWIV is negatively but insignificantly related to future stock returns over the monthly sample analyzed by GS.

[6] In a study independent of ours, Ang et al. (2003) also find that stocks with relatively high past idiosyncratic volatility tend to have lower future returns than stocks with relatively low past idiosyncratic volatility.

The remainder of the paper is organized as follows. We discuss the data in Section I and present the empirical results in Section II. Some concluding remarks are offered in Section III.

I. Data

We use the CRSP value-weighted stock market returns as a proxy for returns on aggregate wealth. Excess returns (ER) are the differences between stock market returns and a risk-free rate, which is also obtained from the CRSP. We aggregate monthly excess returns into the quarterly data through continuous compounding. As in Guo (2002), we define the quarterly realized stock market volatility (MV) as

$$(3) \qquad MV_t = \sum_{d=1}^{D_t} (e_{md} - \bar{e}_{md})^2,$$

where e_{md} is the excess stock market return in day d of quarter t and $\bar{e}_{md}$ is its quarterly average. We obtain daily value-weighted stock market returns from CRSP and assume that the daily risk-free rate is constant within a month. The consumption-wealth ratio (CAY) is obtained from Martin Lettau at New York University. Guo (2002) finds that the stochastically detrended risk-free rate (RREL)—the difference between the risk-free rate and its average over the past 12 months—provides additional information about future stock returns beyond stock market volatility and the consumption-wealth ratio.[7] However, as shown below, our results are not sensitive to whether we include it in the forecasting equation.

We follow GS in the construction of the equal-weighted average stock volatility EWIV defined in equation (1) using the daily CRSP return data, which start from July 1962. As in Campbell et al. (2001), we also calculate a value-weighted average stock volatility (VWIV)

[7] Patelis (1997) suggests that variables such as the stochastically detrended risk-free rate forecast stock returns because these variables reflect the stance of monetary policies, which have state-dependent effects on real economic activities through a credit channel (e.g., Bernanke and Gertler [1989]).

(4) $$VWIV_t = \frac{1}{N_t}\sum_{i=1}^{N_t}\omega_{it}[\sum_{d=1}^{D_t} r_{id}^2 + 2\sum_{d=2}^{D_t} r_{id} r_{id-1}] \quad and\ \omega_{it} = \frac{v_{it-1}}{\sum_{j=1}^{N_t} v_{jt-1}},$$

where v_{it-1} is the market capitalization of stock *i* at the end of the period *t*-1. VWIV starts one period (a month or a quarter) after EWIV because we need the market capitalization data at the end of the previous period. Equations (1) and (4) provide measures of the average stock volatility, which is approximately the sum of stock market volatility and the idiosyncratic volatility. To obtain a direct measure of the latter, we regress the daily excess return on stock *i*, er_{it}, on a vector of daily risk factors, f_t,

(5) $$er_{id} = \alpha + \beta \cdot f_d + \eta_{id},$$

and use the residual η_{id} instead of the raw return r_{id} in equation (1) or (4).[8] We use two sets of risk factors: (1) daily excess stock market return, as in the CAPM and (2) the daily FF three factors. The daily factor data, which start from July 1963, are obtained from Ken French at Dartmouth College. To avoid any confusion, we denote the measure defined by equation (1) or (4) as the average stock volatility if we use raw returns, and as the idiosyncratic volatility if we use residuals from a factor model. In particular, EWIV (VWIV) is the equal-weighted (value-weighted) average stock volatility, EWIV_M (VWIV_M) is the equal-weighted (value-weighted) idiosyncratic volatility based on the CAPM, and EWIV_F (VWIV_F) is the equal-weighted (valued) idiosyncratic volatility based on the FF three-factor model.

[8] Given that loadings on the risk factors, β, might change over time, we also estimate equation (5) using a rolling sample. In particular, at time *d*, we obtain $\hat{\beta}_d$ using the daily data from *d*-130 to *d*-1, and the idiosyncratic shock to stock *i* at time *d* is given by $\eta_{id} = er_{id} - \alpha - \hat{\beta}_d \cdot f_d$. We also require a minimum of 45 daily observations in order to obtain less-noisy parameter estimates. However, using the rolling sample gives very similar results to those using the full sample. To conserve space, we report only the results of the full sample and the results of the rolling sample are available upon request.

Figure 1 plots monthly EWIV (dashed line) and VWIV (solid line), with the shaded areas indicating business recessions dated by the National Bureau of Economic Research (NBER).[9] Both series, especially the former, display an upward trend and tend to rise during business recessions.[10] EWIV is also much higher than VWIV. Figure 2 shows that quarterly EWIV (dashed line) and VWIV (solid line) display very similar patterns to their monthly counterparts in Figure 1. Figure 3 plots quarterly EVIV_F (dashed line) and VWIV_F (solid line).[11] Compared with Figure 2, the idiosyncratic volatility has relatively small spikes during recessions and, especially, during the 1987 stock market crash. These results are consistent with those of Campbell et al. (2001) and GS.

Interestingly, as shown in Figure 4, VWIV_F (solid line) moves closely with stock market volatility (dashed line). In contrast, Figure 5 shows that VWIV_F (solid line) tends to move in the opposite direction with the consumption-wealth ratio (dashed line).[12] The patterns are important for understanding the predictive ability of VWIV_F, which we discuss below. Stock market volatility has a huge spike during the 1987 stock market crash. Following Campbell et al. (2001) and Guo (2002), among many others, we adjust this observation downward in our empirical analysis below.

Table 1 provides summary statistics of the variables used in this paper. To be comparable with GS, we include the monthly equal-weighted average stock volatility, $EWIV^M$, which is

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[9] As in GS, we exclude stocks with less than five return observations within a month. Also, if $\sum_{d=1}^{D_{it}} r_{id}^2 + 2\sum_{d=2}^{D_{it}} r_{id} r_{id-1}$ is less than zero, we drop the term $2\sum_{d=2}^{D_{it}} r_{id} r_{id-1}$ from equation (1) or (4). In the case of value weighting, we also drop stocks for which the market capitalization data at the end of the previous month are missing.

[10] Malkiel and Xu (2003) and Wei and Zhang (2003) provide some rationales about the upward trend in the average and idiosyncratic volatilities.

[11] We find very similar patterns in the idiosyncratic volatility based on the CAPM, which is not reported here.

[12] For illustration, we scale stock market volatility by 8 in Figure 4 and scale the consumption-wealth ratio by 3 in Figure 5.

sampled only in the last month of each quarter. For example, we use the March observation for the first quarter and so forth. The other measures of the average and idiosyncratic volatilities are constructed on a quarterly basis. As shown in panel A, the idiosyncratic and average volatilities, especially if weighted equally, are much higher than stock market volatility. Panel B shows that various measures of the idiosyncratic and average volatilities are highly correlated to each other and are also positively (negatively) correlated with stock market volatility (the consumption-wealth ratio). Campbell et al. (2001) argue that there is a deterministic trend in the idiosyncratic volatility, which might leads to spurious regressions. We confirm that the time trend is highly significant in all cases, and these results are available upon request. Following their advice, we also use the detrended idiosyncratic or average volatility—the residual from the regression of the idiosyncratic or average volatility on a constant and a linear time trend—in our empirical analysis. Panel C reports the cross-correlation based on the detrended volatilities, which is similar to that reported in panel B.

II. Forecasting One-Quarter-Ahead Excess Stock Market Returns

A. Monthly Equal-Weighted Average Stock Volatility Reported by GS : 1962:Q4 to 1999:Q4

Table 2 presents the ordinary least-squares (OLS) estimation results of the forecasting equation

(6) $$ER_t = a + b \cdot EWIV^{M}{}_{t-1} + c \cdot MV_{t-1} + d \cdot CAY_{t-1} + e \cdot RREL_{t-1} + \varepsilon_t .$$

We report the heteroskedasticity-corrected t-statistics in parentheses. To be comparable with GS, we use the same sample period 1962:Q4 to 1999:Q4. Also, as mentioned above, $EWIV^{M}$ is the monthly average stock volatility used in GS, which is sampled in the last month of each quarter.[13] Row 1 shows that $EWIV^M$ by itself is significantly positive with the adjusted R-squared of 4.26 percent. This result is very similar to those reported in Table A1 of GS. However, if we also add stock market volatility, MV, to the forecasting equation, row 2 shows that $EWIV^M$ becomes statistically insignificant, whereas MV is significantly positive. In contrast, $EWIV^M$ remains significantly positive if the forecasting equation includes $EWIV^M$ and either the consumption-wealth ratio, CAY (row 3), or the stochastically detrended risk-free rate, RREL (row 4). Overall, row 5 shows that $EWIV^M$ is insignificantly negative if we control for all the other variables. Similarly, if we drop $EWIV^M$, as shown in row 6, the adjusted R-squared is essentially unchanged, confirming its negligible predictive power. As mentioned above, the deterministic trend in the idiosyncratic or average stock volatility might lead to spurious regressions. To address this issue, we repeat the above analysis using the detrended average stock volatility and report the regression results in panel B. Again, we find that MV always drives out detrended $EWIV^M$. Therefore, the average stock volatility advocated by GS forecasts stock returns mainly because it co-moves with stock market volatility.

B. Monthly Equal-Weighted Average Stock Volatility Reported by GS : Different Samples

To further check the robustness of the results by GS, we also update the sample from 1999:Q4 to 2002:Q4 with 12 additional quarterly observations—the most recent data available to us when the paper was written—and report the estimation results in panel A of Table 3. In sharp contrast with Table 2, row 1 of Table 3 shows that $EWIV^M$ by itself is still positive but no longer statistically significant in the updated sample. We find a similar result using the updated monthly data. It remains insignificant after we control for the other forecasting variables in row 2.

[13] It should be noted that we find very similar results using $EWIV^M$ sampled in the first or second month of each quarter.

However, consistent with Guo (2002), MV is always significantly positive when combined with CAY, although it is insignificant by itself in the updated sample. The recent experience provides a good example to understand the importance of including CAY in the forecasting equation, as advocated by Guo (2003). The positive relation between the average stock volatility or stock market volatility and future returns disappears in the updated sample because stock market prices fell steeply while both the average volatility (Figure 1) and stock market volatility (Figure 4) rose sharply in the past few years. However, this relation is less puzzling if we take into account that CAY indicates that the U.S. stock market has been seriously overvalued before the crash, as shown in Figure 5. Moreover, in Table 3, we find qualitatively the same results in two subsamples: 1962:Q4 to 1982:Q4 in panel B and 1983:Q1 to 2002:Q4 in panel C.

For comparison, we also report the results using the detrended equal-weighted average stock volatility, D_EWIV^M. It should be noted that, if necessary, we add the capital letter D in front of a variable to denote the detrended series. The results are similar to those using the raw average stock volatility, with one exception: The coefficient of $EWIV^M$ is negative in row 2 and, especially, is significantly negative at the 10 percent level in row 7. However, it becomes positive after we take out the linear trend, as shown in rows 4 and 9. These results highlight the spurious regression problem of using the trended volatility measures, e.g., $EWIV^M$, as a regressor in the forecasting equation (6). Therefore, following Campbell et al. (2001), we use only the detrended idiosyncratic volatility in the remainder of the paper. However, unless otherwise indicated, detrending does not affect the results in any qualitative manners.

C. Quarterly Equal-Weighted Average and Idiosyncratic Stock Volatilities

The average stock volatility does not provide information beyond stock market volatility possibly because it is not precisely measured at the monthly frequency. Also, the idiosyncratic volatility based on the CAPM or the FF three-factor model might have better forecasting performance than the average stock volatility proposed by GS. However, Table 4 shows that these considerations do not change the results from the preceding subsections. Panel A presents the results of the detrended equal-weighted quarterly average stock volatility, D_EWIV. Consistent with panel A of Table 3, it is statistically insignificant by itself (row 1) or in conjunction with MV (row 2). It, however, becomes significantly positive when combined with CAY (row 3). But this result merely reflects a close relation between D_EWIV and MV: MV drives out D_EWIV completely if we add both MV and CAY to the forecasting equation (row 4). We find qualitatively the same results using the idiosyncratic volatility based on the CAPM (panel B) and the FF three-factor model (panel C).

D. Quarterly Value-Weighted Average and Idiosyncratic Stock Volatilities

In the preceding subsections, we find that neither the equal-weighted average nor the idiosyncratic stock volatility provides additional information beyond stock market volatility in forecasting stock returns. One possible reason is that equal weighting is a poor measure of the idiosyncratic risk faced by investors because it gives too much weight to small stocks, which are a small share of investors' portfolios. To address this issue, we present in Table 5 the results using the detrended value-weighted quarterly average and idiosyncratic stock volatilities.

Panel A presents the results of the detrended quarterly value-weighted average stock volatility, D_VWIV. Row 1 shows that it is insignificantly and negatively related to future stock returns. Interestingly, it becomes significantly negative when we also add MV to the forecasting equation, with the adjusted R-squared of 5.93 percent (row 2). It should also be noted that MV is significantly positive in row 2, although it is insignificant by itself in this sample, as mentioned above. Therefore, the results of row 2 cannot be attributed to the high correlation between the two variables, as documented in Figure 4 and Table 1. In contrast, D_VWIV is not significant at the 5 percent level if we add CAY and RREL, respectively, to the forecasting equation (rows 4 and 5). That D_VWIV is significantly negative when combined with MV is puzzling because it contradicts the existing theories, e.g., Levy (1978), Merton (1987), and Malkiel and Xu (2001). One possible explanation is that, as mentioned in the introduction, D_VWIV forecasts stock returns because it co-moves with CAY. This conjecture is plausible because, as shown in panel C of Table 1, the correlation coefficient between the two variables is -0.59. Indeed, row 5 shows D_VWIV becomes insignificant after we add MV, CAY, and RREL together to the forecasting equation.[14] Moreover, this result is not sensitive to whether we drop RREL from the forecasting equation (row 6). We reach the same conclusion using the value-weighted idiosyncratic volatility based on the CAPM (panel B) and the FF three-factor model (panel C). Therefore, the value-weighted average and idiosyncratic volatilities don't provide information beyond the forecasting variables advocated by Guo (2003) either.

III. Conclusion

In this paper, we show that, contrary to Goyal and Santa-Clara (2003), there is little empirical support for the hypothesis that poor diversification of investors' portfolios makes idiosyncratic risk an important determinant of conditional excess stock market returns. In

[14] We find that the raw volatility is significant in the forecasting equation. This result is likely due to spurious regressions, as mentioned above. For example, if we add a linear time trend to the equation (6), the raw volatility again becomes insignificant. Moreover, adding the raw volatility does not improve the predictive power in the out-of-sample test. We find very similar results in panels B and C.

particular, we find that, the equal-weighted average and idiosyncratic stock volatilities investigated by GS forecast stock returns mainly because they co-move with stock market volatility. More importantly, in sharp contrast with the positive effect advocated by GS, the value-weighted average and idiosyncratic volatilities are actually found negatively related to future stock returns. Nevertheless, their predictive power is subsumed by the consumption-wealth ratio, and our results thus provide support for the forecasting equation advocated by Guo (2003).

Our empirical results also challenge the existing theories. Given that many investors own only a few stocks—a fact well established by recent authors, e.g., Barber and Odean (2000)—it is puzzling that idiosyncratic volatility has negligible or even negative effects on expected stock market returns. Also, it is not clear why the valued-weighted idiosyncratic volatility is closely related to the consumption-wealth ratio, as shown in Figure 5. Addressing these issues formally is beyond the scope of this paper; we believe, however, they warrant attention in future research.

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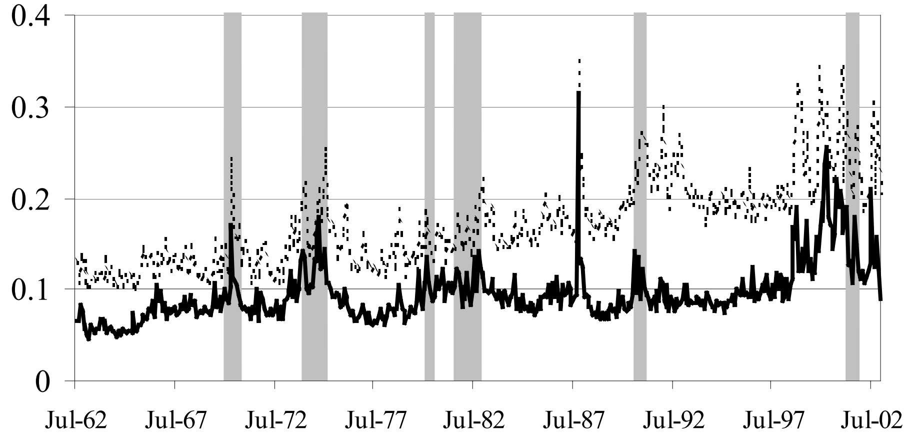

Figure 1. Monthly Average Stock Volatility

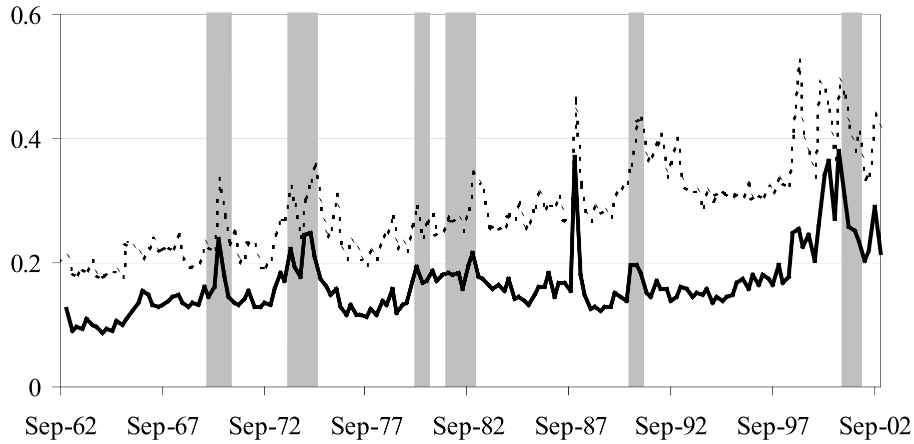

Figure 2. Quarterly Average Stock Volatility

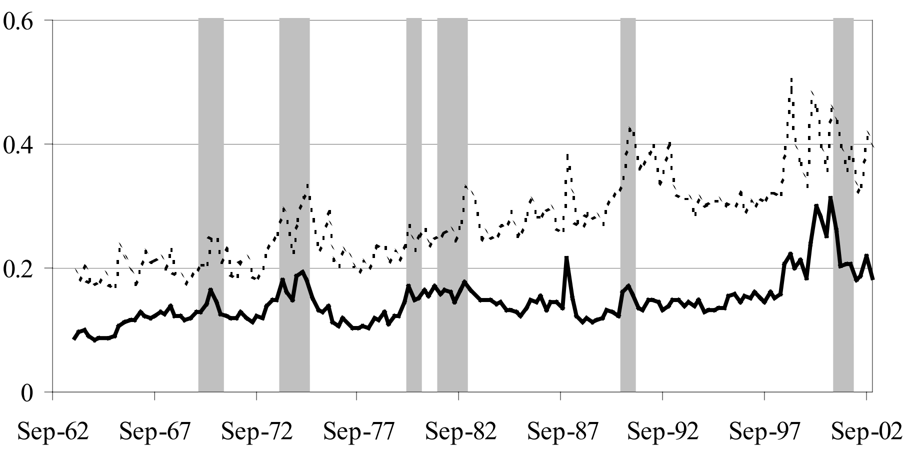

Figure 3. Quarterly Idiosyncratic Volatility Based on the FF Three-Factor Model

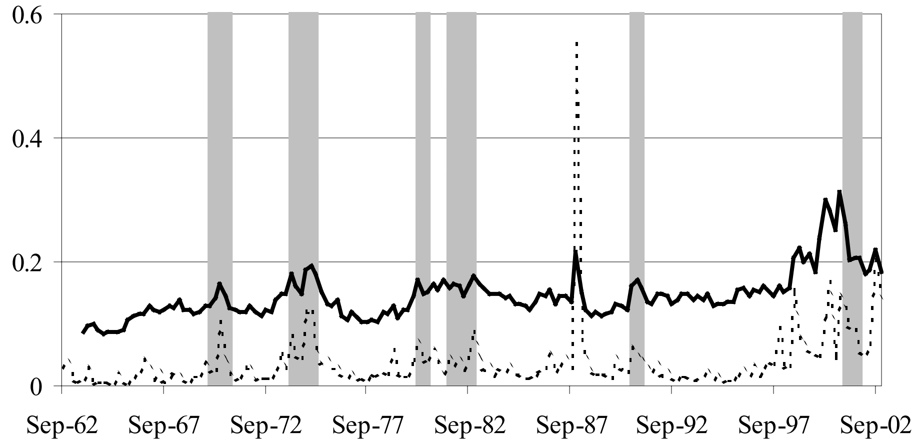

Figure 4. Quarterly Idiosyncratic Volatility and Stock Market Volatility

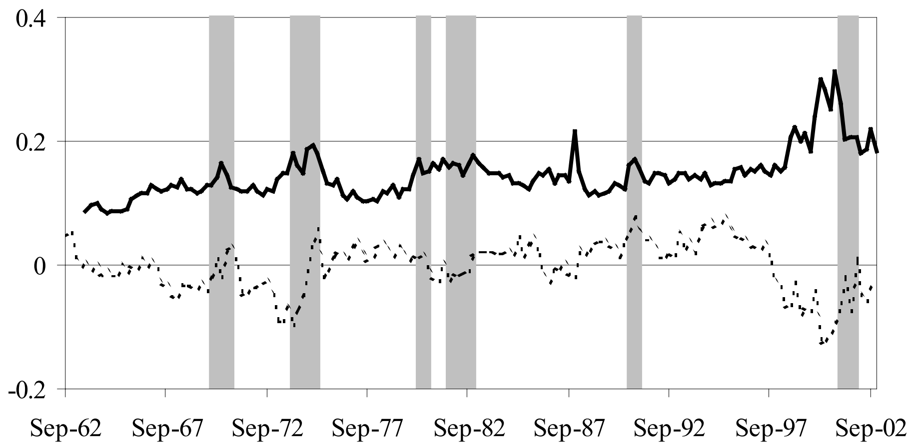

Figure 5. Quarterly Idiosyncratic Volatility and The Consumption-Wealth Ratio

Table 1. Summary Statistics: 1962:Q3 – 2002:Q4

	$EWIV^M$	EWIV	EWIV_F	VWIV	VWIV_F	MV	CAY	RREL	ER
	Panel A. Mean and Standard Deviation								
Mean	0.031	0.088	0.081	0.030	0.023	0.005	-0.001	-0.000	0.013
SD	0.018	0.047	0.043	0.022	0.014	0.004	0.014	0.003	0.087
	Panel B. Cross Correlation: Raw Average and Idiosyncratic Volatilities								
$EWIV^M$	1.000								
EWIV	0.937	1.000							
EWIV_F	0.940	0.985	1.000						
VWIV	0.719	0.786	0.695	1.000					
VWIV_F	0.770	0.810	0.759	0.949	1.000				
MV	0.582	0.666	0.573	0.873	0.771	1.000			
CAY	-0.111	-0.148	-0.086	-0.472	-0.487	-0.408	1.000		
RREL	-0.208	-0.257	-0.275	-0.095	-0.087	-0.113	-0.098	1.000	
ER	-0.03	-0.001	0.076	-0.280	-0.169	-0.388	0.323	-0.258	1.000
	Panel C. Cross Correlation: Detrended Average and Idiosyncratic Volatilities								
$EWIV^M$	1.000								
EWIV	0.859	1.000							
EWIV_F	0.861	0.969	1.000						
VWIV	0.614	0.730	0.586	1.000					
VWIV_F	0.634	0.707	0.618	0.936	1.000				
MV	0.456	0.578	0.443	0.788	0.676	1.000			
CAY	-0.255	-0.315	-0.250	-0.585	-0.647	-0.408	1.000		
RREL	-0.132	-0.204	-0.236	-0.019	0.006	-0.113	-0.098	1.000	
ER	-0.053	-0.016	0.108	-0.326	-0.213	-0.388	0.323	-0.258	1.000

Note: $EWIV^M$ is the monthly equal-weighted average stock volatility sampled in the last month of each quarter. The other variables are constructed quarterly. EWIV (VWIV) is the equal-weighted (value-weighted) average stock volatility; EWIV_F (VWIV_F) is the equal-weighted (valued) idiosyncratic volatility based on the FF three-factor model; MV is stock market volatility; CAY is the consumption-wealth ratio; RREL is the stochastically detrended risk-free rate; and ER is the excess stock market return. EWIV_F and VWIV_F start from 1963:Q3. The detrended volatility in panel C is the residual from the regression of the raw volatility on a constant and a linear time trend.

Table 2. Forecasting One-Quarter-Ahead Excess Stock Market Returns Using Monthly Equal-Weighted Average Idiosyncratic Volatility Reported by GS: 1962:Q4 to 1999:Q4

	$EWIV^M$	MV	CAY	RREL	Adj. R-Squared
Panel A. Raw Average Stock Volatility					
1	1.297				4.26
	(3.066)				
2	0.590	6.230			8.21
	(1.327)	(2.974)			
3	1.062		1.352		7.36
	(2.235)		(2.217)		
4	1.007			-5.406	7.09
	(2.272)			(-2.304)	
5	-0.469	9.824	2.187	-5.013	19.08
	(-1.024)	(4.858)	(3.781)	(-2.410)	
6		8.716	2.017	-4.646	19.23
		(4.936)	(3.809)	(-2.245)	
Panel B. Detrended Average Stock Volatility					
7	1.892				3.96
	(2.583)				
8	0.796	6.348			8.06
	(1.070)	(3.196)			
9	2.057		1.726		9.67
	(2.824)		(2.982)		
10	1.471			-5.509	6.95
	(1.929)			(-2.265)	
11	0.314	8.281	2.013	-4.457	18.76
	(0.455)	(4.364)	(3.821)	(-2.063)	
12		8.716	2.017	-4.646	19.23
		(4.936)	(3.809)	(-2.245)	

Note: The table reports the regression results of equation (6). The heteroskedasticity-corrected t-statistics are in parentheses. See note of Table 1 for the data description.

Table 3. Forecasting One-Quarter-Ahead Excess Stock Market Returns Using Monthly Equal-Weighted Average Stock Volatility Reported by GS: Different Sample Periods

	$EWIV^M$	$D\text{-}EWIV^M$	MV	CAY	RREL	Adj. R-Squared
			Panel A. 1962:Q4 - 2002:Q4			
1	0.391					0.01
	(0.857)					
2	-0.483		6.774	2.464	-4.026	15.36
	(-1.148)		(3.765)	(4.977)	(-1.854)	
3		0.908				0.88
		(1.101)				
4		0.702	4.809	2.452	-3.405	15.46
		(0.951)	(3.334)	(4.996)	(-1.516)	
5			5.572	2.396	-3.657	15.28
			(3.535)	(4.937)	(-1.691)	
			Panel B. 1962:Q4 – 1982:Q4			
6	2.025					1.69
	(1.379)					
7	-2.981		15.206	2.599	-6.821	26.09
	(-1.786)		(4.053)	(3.386)	(-2.664)	
8		2.890				4.08
		(1.913)				
9		1.247	7.968	2.721	-5.579	24.23
		(1.132)	(3.036)	((3.368)	(-1.967)	
10			9.420	2.614	-6.075	24.49
			(4.550)	(3.338)	(-2.213)	
			Panel C. 1983:Q1 - 2002:Q4			
11	0.145					-1.19
	(0.207)					
12	0.330		4.704	2.437	-1.685	7.37
	(0.505)		(2.460)	(2.980)	(-0.259)	
13		0.476				-0.58
		(0.541)				
14		0.477	4.602	2.389	-1.518	7.62
		(0.608)	(2.349)	(3.022)	(-0.460)	
15			5.196	2.380	-1.756	8.26
			(2.275)	(2.976)	(-0.562)	

Note: The table reports the regression results of equation (6). The heteroskedasticity-corrected t-statistics are in parentheses. $D\text{-}EWIV^M$ is the detrended series of $EWIV^M$. See note of Table 1 for the data description.

Table 4. Forecasting One-Quarter-Ahead Excess Stock Market Returns Using Quarterly Detrended Equal-Weighted Idiosyncratic Volatility: 1963:Q1 – 2002:Q4

	D_EWIV	D_EWIV_M	D_EWIV_FF	MV	CAY	RREL	Adj. R-Squared
Panel A. Equal-Weighted Average Stock Volatility							
1	0.268						0.31
	(1.204)						
2	0.068			2.515			0.76
	(0.278)			(1.313)			
3	0.551				2.137		10.18
	(2.592)				(4.004)		
4	0.113			5.154	2.425	-3.477	14.85
	(0.463)			(2.952)	(4.766)	(-1.506)	
Panel B. Equal-weighted Idiosyncratic Volatility Based on the CAPM							
5		0.252					0.02
		(1.042)					
6		0.047		2.764			0.87
		(0.182)		(1.513)			
7		0.521			1.997		8.62
		(2.263)			(3.699)		
8		0.083		5.414	2.376	-3.617	14.51
		(0.326)		(3.235)	(4.565)	(-1.547)	
Panel B. Equal-weighted Idiosyncratic Volatility Based on the FF Three-Factor Model							
9			0.266				0.01
			(1.049)				
10			0.067	2.727			0.88
			(0.256)	(1.525)			
11			0.519		1.954		8.35
			(2.169)		(3.660)		
12			0.077	5.457	2.372	-3.622	14.50
			(0.295)	(3.330)	(4.588)	(-1.540)	

Note: The table reports the regression results of equation (6). The heteroskedasticity-corrected t-statistics are in parentheses. D denotes the detrended series; for example, D-$EWIV^M$ is the detrended series of $EWIV^M$. See note of Table 1 for the data description.

Table 5. Forecasting One-Quarter-Ahead Excess Stock Market Returns Using Quarterly Detrended Value-Weighted Average and Idiosyncratic Volatilities: 1963:Q3 – 2002:Q4

	D_VWIV	D_VWIV_M	D_VWIV_FF	MV	CAY	RREL	Adj. R-Squared
Panel A. Value-Weighted Average Stock Volatility							
1	-0.124						-0.56
	(-0.318)						
2	-1.631			8.539			5.93
	(-2.925)			(3.433)			
3	0.872				2.429		8.71
	(1.823)				(3.652)		
4	-0.141					-5.698	2.78
	(-0.386)					(-2.436)	
5	-0.496			6.988	2.129	-3.659	14.79
	(-0.703)			(2.649)	(3.274)	(-1.720)	
6	-0.546			7.600	2.244		13.75
	(-0.760)			(2.814)	(3.480)		
Panel B. Value-Weighted Idiosyncratic Volatility Based on the CAPM							
7		-0.641					0.24
		(-1.221)					
8		-2.448		7.767			7.85
		(-3.723)		(3.618)			
9		0.931			2.263		7.08
		(1.107)			(2.899)		
10		-0.620				-5.673	3.55
		(-1.257)				(-2.444)	
11		-0.806		6.818	2.027	-3.657	14.99
		(-0.821)		(3.197)	(2.752)	(-1.727)	
12		-0.873		7.383	2.139		13.96
		(-0.866)		(3.359)	(2.920)		
Panel C. Value-Weighted Idiosyncratic Volatility Based on the FF Three-Factor Model							
13			-0.713				0.25
			(-1.192)				
14			-2.690	7.699			7.77
			(-3.686)	(3.627)			
15			1.035		2.265		7.09
			(1.088)		(2.912)		
16			-0.704			-5.698	3.59
			(-1.260)			(-2.458)	
17			-0.891	6.799	2.024	-3.695	14.99
			(-0.818)	(3.225)	(2.751)	(-1.741)	
18			-0.939	7.333	2.147		13.92
			(-0.837)	(3.370)	(2.936)		

Note: The table reports the regression results of equation (6). The heteroskedasticity-corrected t-statistics are in parentheses. D denotes the detrended series; for example, D-$EWIV^M$ is the detrended series of $EWIV^M$. See note of Table 1 for the data description.